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Targeting Assistance to the Poor Using Household Survey Data

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Household survey data from Côte d'Ivoire are used to predict incomes based on observable household characteristics, such as region of residence and characteristics of the household dwelling. These predictions are then used to allocate money transfers to alleviate poverty. Whether one should distribute poverty-alleviating transfers using this method remains to be seen.

Reducing poverty is a major objective of economic policies in both developed and developing countries. It is important that limited government resources be channeled to the poor, but it is not always easy to identify the poor directly.

Which households should be given transfers (such as money, food stamps, vouchers, and rations) when reliable information on incomes is difficult to obtain? How much money (stamps, vouchers, rations) should be given? The answers to these two questions depend on the information available.

Glewwe and Kanaan present a simple method for targeting when income is not observable but other characteristics that are correlated with income can be observed. Using simple regression techniques on comprehensive household survey data taken from Côte d'Ivoire, they predict incomes based on observable household characteristics and distribute transfers on the basis of those predictions. It appears that significant reductions in poverty can be achieved using this method.

Some of the variables that most reliably predicted income level in Côte d'Ivoire were: per capita floor area; whether the household was headed by a member of the Voltaic ethnic group (which is one of the poorest groups); the level of educational attainment of the head of household; whether the household owned a car, a bike, or a refrigerator.

Several problems with this approach are discussed. For example, the cost of gathering information may at times outweigh the benefits. Also, basing transfers on a policy that favors one group over another might lead to public opposition.

This paper is a product of the Welfare and Human Resources Division, Population and Human Resources Department. Copies are available free from the World Bank, 1818 H Street NW, Washington DC 20433. Please contact Brenda Rosa, room S9-137, extension 33751 (48 pages with tables).

Targeting Assistance to the Poor: A Multivariate Approach Using Household Survey Data

by
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and
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Table of Contents

We would like to thank Harold Alderman, Tim Besley, Nanak Kakwani, and Elene Makonnen for comments on an earlier draft of this paper.

I. Introduction

Reducing poverty is one of the major objectives of economic policies in both developed and developing countries. There are many ways to go about achieving this task, each of which has associated costs. To the extent that assistance does indeed reach the poor overall poverty will be reduced, or even eliminated if the funds allocated for this purpose are large enough. However, it is not always easy to identify the poor directly. Given that governments have limited resources it is important that assistance is not mistakenly given to the nonpoor, who may attempt to gain access to benefits by misrepresenting their income status. The task of ensuring that poverty assistance actually reaches the neediest is often referred to as the targeting issue.[1/]

Targeting benefits to reach the poor can be done in many ways. This paper is limited to targeting in the form of transfers (money, food stamps, rations, etc.) given directly to households which are identified as likely to be poor. The relevant questions here are: 1. To which households should one give these transfers, given that reliable information on incomes is difficult to obtain? 2. How much money (or stamps, or rations) should be given? The answers to these questions depend crucially on the information available. This paper presents a method that uses data from household surveys to increase the efficiency of targeted assistance.

The paper is organized as follows. The next section discusses the theoretical issues involved in targeting. Section III provides a method of

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1/ Recent theoretical papers on targeting include Besley and Kanbur (1988), Kanbur (1987), Nicholas and Zeckhauser (1982), Ravallion (1988), and Ravallion and Chao (1988).

targeting using household survey data. Section IV applies this method using data from Côte d'Ivoire. The fifth section discusses some ways in which the analysis could be extended, and the last section concludes the paper.

II. Principles of Targeting Transfers to the Poor

The objective of targeting transfers to the poor is to reduce measured poverty given a fixed amount of money available for such transfers.[2/] This requires an aggregate index, or measure, of poverty for use in comparing the outcomes of different transfer schemes. Formally, let $y = (y_1, y_2, \ldots y_n)$ be the distribution of incomes over the population in question. If an individual has an income which puts him or her below some pre-specified poverty line z, that person is categorized as poor.[3/] The measure of poverty is an index which indicates the aggregate amount of poverty, usually giving heavier weight to those who are deeper in poverty. It is a function of the distribution of incomes y and the poverty line z:

$$P = P(y;z) \tag{1}$$

2/ At this point assume that all transfers must be non-negative, so that the fixed amount of money must be positive. The analysis here can be extended to allow for negative transfers (i.e. taxes), as discussed briefly in Section V.

3/ For clarity of exposition, assume for the moment that we can treat individuals as living in separate households. The framework easily extends to the case where individuals live in households and per capita income is used as a measure of poverty status. This is done in the empirical section of this paper.

Let $t = (t_1, t_2, \ldots t_n)$ designate a vector of transfer incomes, where t_i is the transfer to person i. These transfers are to be given to poor people so that the index $P(y;z)$ is minimized subject to the constraint that total transfers cannot exceed the amount of money available (denoted by T) that purpose:

$$\min_{t} P(y + t;\ z) \text{ conditional on } \Sigma\, t_i \leq T \tag{2}$$

Any individual i with an income above z should not receive a transfer (t_i=0) since that individual is not poor.[4/]

If one knows the incomes y_i for each person this can be efficiently solved given the functional form of the index $P(y;z)$. In most cases the solution would require that the marginal transfer dollar go to the poorest person. Yet in the real world one does <u>not</u> know the incomes of either the poor or the non-poor populations, and both have incentives to understate their incomes in order to obtain more government transfers than they would otherwise be entitled to receive. Targeting thus attempts to reduce <u>expected</u> poverty, $E[P(y;z)]$, given that y cannot be observed but some idea of likely distribution of the elements of y, usually based on observable characteristics of individuals which are correlated with y, can be constructed.[5/]

4/ Virtually all poverty indices follow the focus axiom of Sen (1976) in that individuals with incomes above the poverty line have no effect on the poverty index except to serve as a scaling factor when calculating the incidence of poverty in the total population.

5/ In reducing expected poverty the poverty index will determine the relative value judgments made with respect to different possible outcomes. This is analogous to the role of the utility function when maximizing utility under uncertainty.

Formally, since one does not observe the true y one must treat each element of y (recall that y is a vector of individual incomes) as a random variable for which there exists a joint probability distribution. If one has absolutely no idea about the joint distribution of the elements y, one cannot calculate expected poverty $E[P(y;z)]$ either before or after transfers. Yet if one has some information on this joint distribution expected poverty given a vector of transfers t can be calculated as

$$E[P(y + t; z)] = \int_0^\infty P(y + t; z)\, f(y)\, dy \tag{3}$$

$$= \int_0^\infty \int_0^\infty \ldots \int_0^\infty P(y + t; z)\, f(y_1, y_2, \ldots y_n)\, dy_1 dy_2 \ldots dy_n$$

where f is the joint distribution function of y and the second term denotes a simple notation for the third term.[6]

Equation (3) implicitly assumes that one can identify specific individuals, hence the subscript 1,2,...n. Yet if y is not observed it is unclear how one can distinguish among individuals. Even if one could label individuals, targeting transfers is not possible without some kind of information specific to individuals which: 1. reveals something about their likely incomes; and 2. varies over individuals. Therefore, in order to target transfers one must know the distribution of f <u>conditional</u> on a vector of observable variables x_i (the subscript indicates individual i) which vary

[6] Note that, as in (2), the assumption is being made that y will be unaffected by transfers. The reasonableness of this assumption will be discussed in Section V.

across individuals. Given this one can calculate expected poverty for a given transfer t as:

$$E\left[P(y + t;\ z)|X\right] = \int_0^{\infty} P(y + t;\ z)\ f(y|X)dy \tag{4}$$

$$= \int_0^{\infty} \int_0^{\infty} \ldots \int_0^{\infty} P(y + t;\ z)\ f(y_1, y_2, \ldots y_n | x_1, x_2, \ldots x_n)\ dy_1 dy_2 \ldots dy_n$$

where X is the matrix formed by the vectors x_1 to x_n.

If the variables one observes in each x_i are sufficiently correlated with income (y), the ability to observe x_i at the individual level, coupled with knowledge of $f(y_1 \ldots y_n | x_1 \ldots x_n)$ will allow for the targeting transfers to the poor. One chooses the t that minimizes (4).

Generally speaking, the more variables in the vector x_i the better one's ability to reduce expected poverty given the functional form of f and a fixed amount of transfer funds T, since the minimization of (4) is facilitated by the consequent reduction of the covariance matrix for $f(y|X)$. In other words, more accurate information about the distribution of each y_i will allow for improved targeting of transfers to the poor. One can define this improved accuracy in two ways, the improvement in the reduction of expected poverty, given a fixed amount of funds, from added information, and the reduction in funds required to attain a pre-specified poverty level due to the acquisition of additional information. Define the former as the poverty reduction (PR) benefit of additional information and the latter as the cost reduction (CR) benefit of new information.[7/] They are formally defined as follows:

$$PR(X_2|y,X_1,T,z) = \underset{t}{Min}\ E[P(y + t;\ z)|X_1,T] - \underset{t}{Min}\ E[P(y + t;\ z\ |X,T] \quad (5)$$

$$CR(X_2|y,X_1,T,z) = \underset{s}{Max}(T - \Sigma s_i) \text{ conditional on} \quad (6)$$

$$\underset{s}{Min}\ E[P(y + s;\ z)|X] \leq \underset{t}{Min}\ E[P(y + t;\ z)|X_1,T]$$

where X_1 is the previous set of information, X_2 is the new information, and X, is the combined set of information.[8/] Equation (5) is the difference between the minimization of expected poverty given the information in X_1 and the minimization of expected poverty given that in X. It is always non-negative and should be positive if the additional information in X_2 is useful. Equation (6) shows how much money can be saved when additional information becomes available which allows the government to more accurately target transfers to achieve a pre-specified poverty level.

If one limits oneself to a relatively small amount of information one can directly solve (4) using household survey data given the assumption that the distribution of incomes found in the survey is identical to that found in the population. This has been done by Ravallion (1988) and Ravallion and Chao (1988), who limit their transfer scheme by dividing up the population into 10 mutually exclusive groups and assuming that the only information available is the membership of each individual in each group and the distribution of income

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7/ The cost reduction benefit is essentially the same as Ravallion's (1988) equivalent gain from targeting.

8/ In most cases additional information will consist of adding more variables to the vector x_i.

within each group.[9/]

However, household surveys often provide a fairly large set of information which can be used to predict income levels. In the next section a method is presented which is based on using predicted values of income given a large number of explanatory variables. Except in very special (and unlikely) cases, it is not exactly equivalent to minimization of expected poverty as given in (4), yet in practice it approximates such a minimization and is both intuitively appealing and computationally simple.

III. Multivariate Targeting Using Survey Data

Suppose one could predict the incomes of individuals given a set of explanatory variables. If one took these predictions and distributed transfers to the poor under the assumption that these predictions were in fact their true incomes, the more precise one's predictions the more poverty would be alleviated due to better targeting.

Specifically, assume that the income of household i, y_i can be predicted by a vector of observable variables x_i which vary over households:

$$y_i = g(x_i) + e_i = \hat{y}_i + e_i \tag{7}$$

The error term e_i accounts for the error in the prediction. One does not have to assume that x_i causes y_i, but simply that the variables in the vector x_i

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[9/] In fact, these assumptions allow Ravallion and Chao to calculate actual (as opposed to expected) poverty since all possible outcomes of the joint probability distribution are permutations of each other.

can be used to <u>predict</u> y_i. Given an estimate of the functional form of g, one can use predicted values of the vector y, denoted by $\hat{y}$, to calculate the predicted value of P(y;z), which can be defined as:

$$\hat{P} = P(\hat{y};z). \tag{8}$$

Note that $\hat{P}$ is in general not equal to P(y;z) and is not even necessarily an unbiased predictor of P. This depends on the econometric technique used to estimate the functional form of g and on the functional form of P.[10/] Transfers can then be chosen to minimize $\hat{P}$ subject to the funds available.

$$\min_t P(\hat{y} + t; \ ) \text{ conditional on } \Sigma\, t_i \leq T \tag{9}$$

The effectiveness of this method in targeting transfers can be easily evaluated using data from a sample survey by calculating the index of poverty after implementing the transfers derived from the solution of (9). This amount of poverty can be denoted as

$$P(y + \hat{t};\ z) \tag{10}$$

10/ For example, if P were linear in y and $\hat{y}$ an unbiased predictor of y, $\hat{P}$ would be an unbiased predictor of P. Yet if P is convex in y P is biased downwards due to Jensen's inequality (we are grateful to Tim Besley for pointing this out). However, note that the estimate of poverty when this scheme is implemented (equation (10)) is not necessarily biased even if $\hat{P}$ is a biased estimate of P.

where $\hat{t}$ is the solution to equation (9). Evaluation of the value of additional information can be obtained from equations analogous to (5) and (6) where $P(y + \hat{t}; z)$ replaces $P(y + t; z)$.

At this point it is useful to compare this approach with the theory of the previous section, where expected poverty is minimized over t. The approach taken here minimizes predicted poverty (as defined in (8)) over t, as expressed in (9). Minimizing predicted poverty is a short-cut method that approximates minimization of expected poverty as in (4). It saves one from having to estimate the joint distribution f in equation (4) and requires only the much easier task of estimating g in equation (7). Although, theoretically speaking, one wants to reduce expected poverty with one's targeting procedure, this requires knowledge of the joint distribution of incomes y conditional on X, which is difficult when X contains several independent variables.[11/] The reduction of predicted poverty is more tractable and equation (10) can be used to give an exact measurement of targeting accuracy over the survey sample.[12/]

Once one has decided to go this route some thought must be given to

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11/ In principle one could use the method of Ravallion as long as one's information set X was restricted to categorical variables so that the entire population could be divided into a finite number of groups. Applying this method would entail a direct minimization of expected poverty as in (4). However, if X contains continuous variables one cannot apply the method without losing some information. Further, Ravallion's method has no framework for testing the statistical significance of the benefit from adding new information, while the method used here can test the statistical significance when estimating g in equation (7).

12/ Note that it makes little sense to calculate the joint distribution of the predicted values of y since cross-sectional regression techniques assume no correlation across y_i's and the distribution of the point estimates of each y_i result from distributional assumptions on e_i in (7), which are difficult to verify.

properties which the observable variables (X's) should have. First, each variable must be correlated with income, so that the variation in the error term e_i in (7) is reduced when the variable is added to the existing set, which in turn implies that reducing predicted poverty will be more highly correlated with reducing actual poverty. Second, each variable should truly be easily observed, so that it cannot be hidden and/or misrepresented by the individuals. For example, if one decides to give transfers to everyone who does not own a certain type of luxury good, such as a car, individuals with cars may be able to hide them and deny that they own a car when screening for eligibility takes place. Third, the variable should not easily be changed by the household. Using the above example, even if it were easy to identify car ownership, some households may actually sell their cars and hire taxis if the added cost were outweighed by the gain from becoming eligible for transfers.

To estimate incomes as in (7) one needs a household survey with the following characteristics. First, the survey must be a random sample from the area under consideration. For example, if one wants to devise a nationwide targeting scheme the survey must be a sample from the entire country. Two, the income data (or expenditure data, see below) must be relatively accurate, otherwise it will introduce another source of error and in addition will make it more difficult to judge, via equation (10), how accurate the targeting really is. Third, the survey must contain a variety of explanatory variables which can be effectively used as the $\mathbf{x}_i$ vector.

With such data simple econometric techniques can be used to predict $\mathbf{y}$ given a matrix $\mathbf{X}$. Since the primary interest is predictive accuracy, rather than estimating any kind of causal structure, the main immediate objective is a good statistical fit as measured by summary statistics such as the correlation coefficient (R^2). As long as a variable on the right hand side of the regression meets the three criteria presented above one can use it to predict y. For estimation one can simply use ordinary least squares (OLS) techniques, so that one estimates a parameter β under the assumption that $g(x_i) = \beta x_i$. [13/] These OLS estimates of income can then be used both to determine whether a house should get any benefits and, if they should, what the level of benefits should be, by the solution of (9).

Before beginning the data analysis in the next section, three issues need to be discussed, the use of expenditure data instead of income data, the treatment of household size, and the choice of poverty index. In any study of poverty one is ultimately concerned with welfare levels, and income is often used as an indicator of them. Yet there are several reasons why it is better to use expenditure levels rather than income levels. First, for purely theoretical reasons, income only generates welfare if it is actually used to raise consumption levels. On the other hand expenditures are closely tied with consumption levels and are thus more appropriate from a theoretical level. The inaccuracy of income for measuring welfare levels is especially true of farmers and other persons whose income fluctuates from year to year, and such people are often found in developing countries. A more compelling reason to use expenditure rather than income data is that the latter is often under-reported by survey respondents who fear that the income data will be

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[13/] Note that x_i may include quadratic terms, interaction terms, etc. and thus βx_i can approximate any functional form as in a Taylor expansion.

used for tax purposes. Yet it is reasonable to assume that they are much less likely to under-report expenditure data because it is gathered by asking many questions on specific items and thus usually does not trigger fears of tax increases. Thus, the empirical part of this paper examines expenditure levels rather than income levels.

Up to this point the discussion has assumed that individuals do not live together in households, but of course they do. The easiest approach to take here is to divide total consumption by household size and use this as a measure of each individual's welfare. This is not completely satisfactory because expenditures may not be divided up equally among household members and in addition there are likely to be economies to scale so that larger households tend to have higher welfare levels than are indicated by per capita consumption figures. Unfortunately, the former problem is almost impossible to solve with most household data sets since they usually do not have information on individual consumption. The latter problem can be resolved only by estimating equivalence scales, which is often a risky venture (cf. Pollak and Wales, 1979). In order to concentrate on the issue of targeting we will assume throughout the paper that per capita expenditures are a valid measure of each household member's welfare.

One final issue must be settled before empirical work can begin: Which index of poverty should be used? There is increasing support for the Foster-Greer-Thorbecke (FGT) class of measures since they are group decomposable and include some commonly used measures as special cases. In addition, this family of measures is not known to have any obvious disadvantages. Hence it is convenient to use them here. The family of measures is defined by Foster, Greer and Thorbecke (1984) as:

$$P_\alpha(y;z) = \frac{1}{n}\Sigma\left(\frac{g_i}{z}\right)^\alpha \qquad \begin{aligned} g_i &= y_i - z \text{ if } y_i \leq z \\ &= 0 \qquad \text{if } y_i > z \end{aligned} \tag{11}$$

where α is a constant term which can be set at different levels. In general, the higher α is the more weight one gives to the poorest of the poor. If α=0 then the FGT measure becomes the headcount ratio, i.e. the proportion of people in poverty. If α=1 then (11) becomes the income gap ratio, i.e. the minimum amount of money needed to bring the incomes of all the poor up to the poverty line as a fraction of the total amount of money in society if everyone had just enough money to put them over the poverty line.

The headcount is universally recognized as a poor index of poverty because it completely ignores the depth of poverty among the poor. The income gap ratio corrects for this but is sometimes criticized for ignoring inequality among the poor. For example, two persons whose incomes are $50 below the poverty line are treated the same as one person with an income $99 below the poverty line and another with an income $1 below the poverty line. If α is greater than 1 the FGT indices show more poverty when greater inequality is found among the poor, *ceteris paribus*. This paper will use the FGT measures for three values of α: 1, 2 and 3. Thus the income gap ratio as well as two indices which are sensitive to inequality among the poor are used. For all three values of α the poverty minimizing strategy is to give the marginal transfer dollar to the poorest persons.[14/]

IV. Application of the Method to Survey Data from Côte d'Ivoire

In this section the application of the method presented in Section III is applied to data from the 1985 Côte d'Ivoire Living Standards Survey (CILSS), which is described in detail in Grootaert (1986) and Ainsworth and Muñoz (1986). The choice of country is primarily due to data availability, yet it is of some interest to apply the method to an African country since poverty is quite severe in many African countries, though Côte d'Ivoire is relatively well off by African standards. The variable to be predicted is per capita household expenditures, which includes imputed values of owner-occupied housing in urban areas. The construction of the expenditure variable is explained in detail in Glewwe (1987) except, unlike in that paper, household equivalence scales are not employed here.

At this point it is instructive to discuss the Ivorian economy briefly. Côte d'Ivoire is found in West Africa on the Gulf of Guineau. It received its independence from France in 1960 and up to the late 1970's was considered to be one of Africa's success stories (cf. den Tuinder, 1978). Its main export crops are coffee and cocoa. Since the early 1980's the economy has declined, in part due to declining prices of coffee and cocoa. Yet it is still better off than most other West African countries and has a relatively high proportion of the population in urban areas, about 43%. The vast

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[14/] For the income gap ratio this strategy is sufficient but not necessary - one need only ensure that all transfers go to individuals whose incomes are below the poverty line.

majority of the poor are found in rural Côte d'Ivoire (cf. Glewwe, 1987), and a disproportionate number are found in the northern savannah areas which are too dry for cocoa and coffee cultivation. This paper will investigate targeting in both urban and rural areas even though the latter are much better off than the former.

A. Welfare Levels and Urban Households' Characteristics

The first step in applying the method of the previous section to urban areas in Côte d'Ivoire is to estimate (7). The explanatory variables used are defined in Table 1. Table 2 presents regressions of the logarithm of per capita household expenditures on different sets of explanatory variables. These variables can be grouped into five categories: (a) regional dummy variables; (b) characteristics of the household's dwelling and the source of the household's drinking water; (c) ethnic origin of the head of household; (d) level of education of the head of household; (e) ownership of durable goods by the household. The variables in categories (a), (b) and (c) should be relatively easy to observe and indeed can usually be observed directly. However, the level of education of the head of household and the ownership of certain durable goods may be more difficult to obtain and could conceivably be disguised. Of course, there exist other variables, such as net savings, which are likely to be highly correlated with levels of welfare. These are not included because of the difficulty of obtaining accurate information on them.

The regression in column 1 of Table 2 (Model 1) includes only variables in categories (a), (b) and (c). Variables which had relatively weak explanatory power in preliminary regressions were excluded. Only one regional dummy variable was statistically significant - households in the East Forest (Southeast) region of Côte d'Ivoire are relatively worse off, *ceteris paribus*. Turning to the characteristics of the dwelling, it is surprising that the log of the floor area is not a good indicator of household welfare. It will be seen below that per capita floor area performs much better. Two variables which are better predictors of household per capita expenditure levels are dummy variables which indicate whether the dwelling is a single house or an apartment (HOUSE and APT, respectively). The alternative living arrangement is sharing a compound with other families, which is apparently viewed as less desirable and consequently is associated with lower per capita incomes.

Dwelling quality also provides information on households' living standards. Wood or stone walls, a cement roof, and a flush toilet are all strongly associated with higher levels of household welfare. Windows with no covering are relatively undesirable and thus have a weakly negative predictive power. Households whose main source of water is a well without a pump have lower levels of welfare while those whose main source of water is an indoor faucet have higher levels. Only one ethnic group variable had substantial explanatory power, households headed by a member of the Voltaic ethnic group are significantly worse off.

Education levels are often strongly correlated with the living conditions of households since more educated individuals tend to have higher incomes. The second column of Table 2 (Model 2) adds variables indicating the education level of the head of household. Households whose head has attained a junior secondary, senior secondary, or university level of education have higher levels of welfare than otherwise identical households with no education. If such information could be obtained accurately at a low cost, targeting of transfers would be enhanced. Column 3 of Table 2 (Model 3) focuses on the ownership of durable goods. Ownership of a car or refrigerator is strongly associated with higher levels of welfare, but bicycle ownership indicates lower levels. Thus data on the possession of these goods may further enhance targeting.

It was seen above that a dwelling's floor area had little explanatory power. It turns out that a better indicator is floor area per capita, as confirmed in column 4 of Table 2 (Model 4). Yet this requires knowledge of household size, and it is possible that households could misrepresent this. In any case, the value of accurate information on household size is evident in this regression. The last column of Table 2 includes all variables discussed so far. If all this information can be obtained fairly accurate predictions on per capita expenditure levels can be obtained, as indicated by the R^2 coefficient of 0.654.

B. Welfare Levels and Rural Households' Characteristics

The 1985 CILSS data include community characteristics from the rural areas sampled, as well as data on farming activities. One can use these data for regressions in rural Côte d'Ivoire. The new explanatory variables are defined in Table 3 and the regressions are given in Table 4.

The first column in Table 4 (Model 1) gives the basic regression. Examining first dwelling characteristics, it is surprising that floor area is negatively associated with per capita expenditures. Yet recall that floor area per capita is perhaps a better indicator of welfare. This is examined below. Most of the other estimated parameters for variables representing dwelling characteristics have the expected signs, but often with low t-statistics. As with urban areas, single homes, apartments and flush toilets are positively associated with household welfare, while adobe walls, water from wells without pumps[15] and windows with no coverings are negatively associated. Another weakly positive indicator is bamboo walls, while negative indicators are water from wells with pumps, bamboo floors and the complete absence of windows in the dwelling. More success in predicting per capita expenditures comes from ethnic group dummy variables - Akan, Northern Mande, Voltaic and non-Ivorian (i.e. immigrants from neighboring countries) households tend to be worse off relative to other ethnic groups.

Turning to the community characteristics, welfare levels are negatively correlated with the distance from Abidjan, perhaps due to either the gradual spread "modernizing influences" from Abidjan to the rest Côte d'Ivoire or to poorer soil quality as one moves from south to north. Communities where Islam is the predominant religion tend to be better off, but not significantly so. Households residing in communities whose major crop is cocoa have, on average, higner levels of welfare, which may reflect the benefits of living in areas well suited to cultivating this lucrative crop. Note that after controlling for these effects the East Forest area is relatively worse-off relative to the rest of the country. Finally, distance

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[15] This is grouped with water from river or other natural source, since the coefficients on both these dummy variables were virtually identical.

to markets is negatively associated with household welfare, while the correlation with adult male wage rates is positive.

The variables discussed so far should be relatively easy to observe. The second column of Table 4 (Model 2) examines the extent to which accurate information on land holdings can improve the predicative power of the regression. Data on household land planted in coffee offers no predictive power, but land planted with cocoa and other types of cultivated land are positively associated with welfare levels. In contrast with urban areas, information on the education of head of household has a much lower degree of explanatory power in rural areas, as seen in column 3 (Model 3). This may be due to the relatively small number of better educated individuals in rural Côte d'Ivoire. Examining the durable items' coefficients in column 4 (Model 4), one sees that, in contrast to the case of urban households, the parameter for ownership of a refrigerator is no longer significant, perhaps reflecting the general lack of refrigerators in rural areas.

The fifth column of Table 4 (Model 5) clearly demonstrates that per capita floor area has strong predictive power, which suggests that if one can get reliable data on household size, one can better target benefits to the poor. Finally, the last column of Table 4 shows that with all of the variables combined the R^2 coefficient reaches 0.319. Compared to urban households, the ability to predict household expenditure variables based on easily observable household characteristics is relatively poor. This suggests that targeting transfers to the poor in Côte d'Ivoire might prove to be easier in urban areas, even though the vast majority of the poor are in rural areas.

C. Targeting Transfers in Urban Côte d'Ivoire

Using the regressions given in Table 2 one can calculate (10), poverty after transfers, where transfers are based on predicted income levels, for urban Côte d'Ivoire. The relevant calculations are given in Table 5. A poverty line of 148,690 CFA Francs per capita per year is used, which classifies 30% of the urban population as poor.[16/] Turning to the top half of Table 5, assume that 10,000,000 CFA Francs are available for transfers.[17/] The first row of Table 5 calculates poverty, using equation (11), for three different values for α. As α increases the poverty index declines, yet this has no meaning whatsoever because the only relevant comparisons of levels of poverty indices are within a given value of α. Yet, changes, in levels can be compared for different values of α, as will be done below.

The remaining rows in top half of Table 5 show poverty levels, calculated from the CILSS data, when 10 million CFA Francs are available for transfers to the poor with varying amounts of information. In the row labeled "untargeted" it is assumed that no information is available, so one has no choice but to give everyone an equal transfer regardless of expenditure level. This untargeted approach reduces poverty by a relatively small amount - between 5% and 8% for different values of α (see figures in parentheses). If instead one uses the predicted income from the regression in Column 1 of

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16/ Any poverty line embodies a value judgment regarding who is poor. We have chosen this poverty line for expositional purposes.

17/ Since the CILSS is a random sample of approximately 0.13% of the Ivorian population, 10,000,000 CFA applied to reducing poverty in the sample is equivalent to 7.83 billion CFA (about $20 million) on a nationwide basis.

Table 2, call it Model 1, poverty can be reduced substantially, from a 10% decline for $\alpha = 1$ to a 22% drop for $\alpha = 3$.

The value of having additional data on either the head of household's education, ownership of durable goods, or household size (in order to calculate per capita floor area) can be seen in the rows marked Model 2, Model 3 and Model 4, respectively. The information on the household head's education reduces poverty somewhat beyond the reduction from Model 1 information alone, but knowledge of durable goods owned by the household has little effect, despite strong t-statistics in Table 2. Further investigation revealed that this greater predictive power from information on durable goods took place primarily at the wealthier end of the distribution and thus contributed very little to distinguishing the poorest households from the rest of the population.[18/] Thus although the R^2 coefficients in Table 2 are often highly correlated with targeting accuracy, a generally better statistical fit may be of little use if it takes place at the higher income levels. Data on per capita floor area (Model 4) allow for a greater reduction in poverty than data on the education of the head for $\alpha = 1$ and $\alpha = 2$, but have virtually the same reduction for $\alpha = 3$. Finally, the row marked Model 5 shows how much poverty can be reduced if all three sets of variables can be observed.

At this point it is useful to say something about the difference α makes when measuring poverty. Recall that the higher α is, the more weight placed on the poorest of the poor. In all the "models" of Table 5, and in the

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18/ When Model 3 was re-estimated using only the poorest 30% of the population the t-statistics on all three durable goods were insignificant.

untargeted and perfect targeting cases as well, the higher α is the more poverty can be reduced, in percentage terms, with a given amount of money. This reflects the fact that the higher α is, the greater the total "amount" of poverty is due to the poorest of the poor, and consequently the more one can do, in percentage terms, with a fixed amount of money as long as it is well targeted toward the poorest groups. Yet, relative to the poverty reduction that would take place if perfect targeting were possible (i.e. if one could observe expenditure levels directly), targeting under imperfect information is more difficult the higher α is. This is due to the fact that at lower values of α targeting need not be very accurate as long as it gets to someone who is poor (e.g. when $\alpha = 1$), while higher values of α require greater precision to target the poorest of the poor. Thus the effectiveness of targeting with imperfect information depends on the value of α (a normative judgment) and on whether one's goal is stated relative to zero poverty or relative to the poverty that would prevail if perfect targeting were possible.

The second half of Table 5 repeats the analysis assuming total transfer funds are 20,000,000 CFA Francs. The same general conclusions hold, but it is clear that doubling the amount of money does not double the reduction in poverty under imperfect targeting.[19/] As one might expect, as more money is added to the transfer fund the marginal effect of a given amount of money on poverty decreases. This decrease in the marginal effect is relatively weak for $\alpha = 1$, since that measure of poverty does not distinguish

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[19/] Untargeted transfers roughly have a double effect, while perfectly targeted transfers by definition have a double effect when $\alpha = 1$, but must have decreasing returns for $\alpha > 1$.

between the marginal dollar given to a very poor person and that given to only a mildly poor person. As α becomes larger, doubling the amount of money clearly does not double the decline in poverty since poverty indices with high values of α put more weight on giving the first funds to the neediest households. Note also the perverse result that poverty reductions from model 3 are lower than those from Model 1 even though the former employs more information and has a more accurate fit as measured by the R^2 coefficient. As was already seen with Model 3 above, a better fit for the entire range of rich and poor households may not fit so well for the poorest households, and in this case the fit on the latter actually becomes worse. This leads to an important result - a good information set for targeting transfers must be measured only in terms of its reduction in measured poverty, not in terms of a regression's overall predictive power.

Table 6 calculates poverty reductions, as defined in equation (5), for the different models.[20/] Recall that poverty reductions depend on the information already available (X_1) as well as the new information (X_2). The figures in Table 6 are calculated with respect to two initial information sets: no information at all, which corresponds to untargeted transfers, and information limited to regional location, dwelling characteristics and household water supply, and ethnic background of households, which corresponds to Model 1. Take the case where 10 million CFA Francs are available for transfers, which is shown in the top half of Table 6. Relative to no information at all, the various models reduce poverty by 6-10% for $\alpha = 1$ to

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20/ Note we replace $P(y + t;z)$ with $P(y + \hat{t};z)$, as explained in Section III.

15-23% for $\alpha = 3$. Of course, perfect information reduces poverty much more. Relative to the information set included in Model 1, the new information embodied in Model 3 is almost inconsequential, while Model 2 does somewhat better and Model 4 better still. The results when 20 million CFA Francs are available show the same trends, except it is worth noting that using Model 3 actually raises poverty relative to Model 1 despite its larger information set, the possibility of which was explained in the preceding paragraph.

The calculations offered so far are of some interest but the real question faced by policy makers is: which types of information are worth collecting? Presumably one can get estimates of the marginal cost of collecting some additional amount of information on households, but what is the marginal benefit? This question can be answered using calculations of cost reductions, which were defined in (6) (cf. footnote 20). It is crucial to realize that cost reductions, as seen in equation (6), depend on: 1. The poverty line chosen (z); 2. The definition of poverty used (in this case the different values of α); 3. The amount of money available for transfers (T); and 4. The initial set of information (X_1). The difference these make is seen in Table 7, where all these vary except the poverty line itself. The poverty line chosen, as well as the poverty definition, are pure value judgments. The amount of money available is the product of a political process which itself embodies value judgments. Yet the initial set of information can be constructed, starting with very low cost information (such as region of residence) in a relatively objective manner. The general rule is: if the money saved, as calculated in (7), is greater than the marginal cost of collecting the additional information, the data should be collected. This can be determined using comprehensive household survey data, as done here.

The figures in the top half of Table 7 give the amount of money which can be saved from new information, starting from a base of 10 million CFA Francs. These figures apply to the sample only, and to obtain figures for all Côte d'Ivoire they should be multiplied by 769 (cf. footnote. 17). Taking the initial case of no information (i.e. completely untargeted transfers), about 6-9 million of the original 10 million CFA Francs (5-7 billion CFA Francs for all Côte d'Ivoire) can be saved using the various targeting models. This is a substantial drop in costs and one would think that the cost of gathering the information is likely to be much less. In many cases much of the information required may already be available from national census data (e.g. housing characteristics) and if not the marginal cost of amending the census to collect it may be rather small. It is also interesting to note that, for the case of no information, differences in the value of α do not seem to make a big difference in terms of cost reductions. Thus, one could go ahead with a targeting scheme even if ones value judgment regarding the proper value of α is not fully thought out.

Turning to the situation where initial information consists of the variables in Model 1, the marginal cost reduction gains of new information are relatively low, but still substantial. There is also more variation across α, especially for Model 2. It is useful to take one example, the value of knowing household size, which allows one to create the per capita floor area variable. Turning to Model 4, between 1.8 and 2.6 million CFA Francs could be saved if accurate information on household size were collected to supplement data used in Model 1. Extrapolating for Côte d'Ivoire as a whole, the savings would amount to between 1.4 and 2.0 billion CFA Francs. In other words, as indicated by the figures in parentheses, the amount of transfers could be cut by 18-26% without reducing poverty if information on household size were available.

The bottom half of Table 7 presents cost reductions when the amount originally available for transfers is doubled to 20 million CFA Francs. For the case where no information was originally available, the savings from new information are slightly less than double those where no information is available with 10 million CFA Francs. When initial information consists of the data used in Model 1, moving from 10 to 20 million CFA Francs usually increases savings but not always. For example, Model 3 is dominated by Model 1 at higher levels of transfer.

D. Targeting Transfers in Rural Côte d'Ivoire

Using the regressions shown in Table 4, one can examine the effect of targeting on poverty in rural Côte d'Ivoire. Table 8 shows targeting effectiveness for transfers of 10,000,000 and 20,000,000 CFA Francs. The poverty line which classifies 30% of the rural population as poor (87,790 CFA Francs per capita) is well below the corresponding line for the urban population. Note that initial poverty levels are higher in rural areas relative to urban areas even though both were given a 30% cut off line. This indicates that the poor in rural areas are deeper in poverty, relatively to their 30% line, than the poor in urban areas relative to their 30% line. The top half of Table 8 shows changes in poverty when 10,000,000 CFA Francs are targeted using various information sets. The untargeted allocation reduces poverty by 5% to 10% for different values of α. If Model 1 is used, poverty can be reduced from 14% for $\alpha = 1$ to 26% for $\alpha = 3$.

The value of adding the information sets relating to land holdings, head of household's education, ownership of durable goods or household size can be seen in the rows for Models 2 to 5, respectively. Clearly, none of these models leads to a significantly greater reduction in poverty than that achieved by the basic model. In fact, whereas Model 2 and Model 4 reduce poverty marginally relative to Model 1, Models 3 and 5 perform worse. Further investigation revealed that when the regressions for Models 2, 3, 4 and 5 are run for the poorest 50% of the population, the predictive power of Models 2, 3 and 4 improve very little over that of Model 1, and the predictive power of Model 5 becomes worse. The bottom half of Table 8 repeats the analysis with 20 million CFA Francs. As in urban areas, doubling the amount of money for transfers does not double the effectiveness of targeting.

Table 9 gives poverty reductions resulting from increased information in rural Côte d'Ivoire. Models 3, 5 and 6 are omitted from the table because they performed worse in reducing poverty than Model 1. As was apparent in Table 8, it is difficult to improve on Model 1 in rural areas. Of course, this does not mean that it is harder to target in rural areas; poverty reductions, in percentage terms, are of the same order of magnitude with Model 1 in rural areas as they are with Model 4 in urban areas. The important lesson here is that the goodness of fit of different regressions across different regions (e.g. urban vs. rural) does not necessarily indicate the potential for poverty reductions. In the case of Côte d'Ivoire, it is harder to predict accurately the per capita expenditure levels of rural residents, relative to their urban counterparts, but this difference in accuracy disappears if one confines the regressions to the poorest 30% of the population in each area (in such cases R^2 ranged from 0.20 to 0.25 in both urban and rural Côte d'Ivoire).[21/]

Finally, Table 10 presents cost reductions possible in rural areas. They are of the same magnitude as those in urban areas - between 6 to 8 million out of an initial 10 million CFA Francs can be saved if targeting is done according to the method presented in this paper. If initially 20 million CFA Francs are available, about 13 to 14 million can be saved by targeting. At first, it may seem contradictory that Model 1 is superior to Models 2 and 4 in terms of cost reductions (Table 10) but is inferior in terms of poverty reductions (Table 9). The difference is explained in that Model 1 can reduce poverty less effectively than Models 2 and 4 when 10 million CFA Francs are available but more effectively if about 2.5 or 3 million CFA Francs are available (this latter range is dictated by the need to match the poverty level, as given in the second row of Table 8, attained by untargeted transfers of 10 million CFA Francs).

As in urban areas, if the information necessary can be collected at a cost smaller than the cost reductions shown in Table 10, the data should be gathered. This is analogous to standard cost-benefit analysis procedures. Note, however, that it is the marginal increment in savings that is relevant for the decision rule. Suppose, using the numbers in the top half of Table

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21/ It was thought that improved targeting might result if (7) were estimated using only the poorest 30% or poorest 50% of the households in the sample. In principle this could work but in fact it did not.

10, it would cost 4 million CFA Francs to gather the data needed to implement Model 1, and 6 million CFA Francs to implement Model 2. Even though one can save money, relative to untargeted transfers, by implementing Model 2, one should only implement Model 1 because, relative to Model 1, Model 2 does not save an additional 2 million CFA Francs (and in fact results in a loss of 400,000 CFA Francs).

E. Allocating Funds Between Urban and Rural Areas

So far this section has treated urban and rural areas separately. This was done mainly for purposes of exposition. In fact policy makers are likely to be faced with the question of how much transfers should go to urban areas and how much should go to rural areas. In this subsection a common poverty line is drawn for all of Côte d'Ivoire to see, given the models calculated above, how a given amount of money can be targeted across both urban and rural areas in order to reduce poverty. A national poverty line of 110,000 CFA Francs is used, which classifies 30% of the population as poor.

Abstracting from information costs, if one had 10 million or 20 million CFA Francs, how should the funds be split up between urban and rural areas under the system of targeting presented in this paper? Clearly, one should use the best model available for both urban and rural areas and split the funds up in a way which minimizes nationwide poverty. Employing Model 5 in urban areas and Model 1 in rural areas, if one has 10 million CFA Francs poverty is minimized by targeting 9 million in rural areas and only 1 million in urban areas. The split with 20 million CFA Francs is even more lopsided - 19 million should go to rural areas and only 1 million in urban areas. The value of α did not matter in either case.[22/] Thus even though one can better predict household expenditure levels in urban areas, one cannot do it better among the poor in urban areas and thus almost all transfer funds should be given to rural residents. This simply reflects the fact that the rural poor are much poorer than the urban poor. Of course, if ones targeting was much more accurate in urban areas, an optimal split of funds may lead to substantial funds going to urban areas even if rural areas were poorer, which at first glance is somewhat counterintuitive.

Yet when policy decisions are made, one cannot abstract away from information costs. If it costs 2 million CFA Francs to collect the necessary data in urban areas, and perhaps 10 million in rural areas, the 10 million may be better used on targeting in urban areas. Or, if the costs are 2 million for both areas, the 2 million to collect data in urban areas may be better spent in raising the total amounts transfered to rural areas. Thus, marginal analysis is also essential for decisions on how to split funds between urban and rural areas. In fact, it is more useful to pose the problem in terms of funds available both for collection of new information and for transfers, so that there are 4 possible uses of funds: gathering information in urban areas, gathering information in rural areas, transfers to urban areas, and transfers to rural areas.

22/ These figures were calculated by increments of 1 million Francs, and thus are not exact. If finer increments were used the value of α could matter slightly.

V. Extensions and Complications

It is hoped that the discussion in the previous sections has shed new light on the problem of reducing poverty in both developed and developing countries. Yet it must be admitted that the exposition proceeded rather smoothly in certain places because certain issues and problems were set aside, both explicitly and implicitly. In this section a variety of complications, as well as extensions, of the procedure taken here will be presented, primarily in order of simpler issues first followed by tougher ones later.

Recall in Section II that it was assumed that transfers are non-negative. Of course, negative transfers are nothing other than taxes. Allowing for negative transfers is conceptually not that difficult, but leads to the more difficult problem of how much money is really available for transfers to the poor. It is useful to distinguish between two types of negative transfers - those which leave the person above the poverty line and those that push him or her below the line. The first type have no effect on the poverty index and thus, to the extent that such taxes can be collected, they merely raise the amount of money available for transfers (T). Once it is possible that negative transfers leave some individuals below the poverty line, one must explicitly choose a set of positive and negative transfers which minimize poverty. At this point one is very close to the literature on optimal taxation (cf. Newberry and Stern, 1987). Yet much of that literature assumes that incomes are observable - once one assumes that they are not the analysis becomes correspondingly more complicated. Suffice it to say at this point that the issues taken up in this paper ultimately fall into a yet relatively new area of optimal tax/transfer policy for the case where incomes are unobservable (cf. Radian, 1980).

A second issue which has implicitly been ignored is whether the objective of minimizing poverty in society conflicts with other principles, particularly the principle of equal or nondiscriminatory treatment of individuals by the government. Use of dummy variables for ethnic groups helps in targeting transfers, but amounts in practice to giving or withholding money to people in part on the basis of which group they belong to. In many countries with diverse populations this practice could quickly lead, quite literally, to riots in the streets. Malaysia is one example of a country where one ethnic group (Malays) has been explicitly favored by the government, but at a cost of resentment and hostility from the other ethnic groups in the population (principally Chinese and Indian). As will be discussed below, one may want to hide the "formula" or "formulas" by which transfers are being made, but this may be very difficult to do.

There is a technical problem related to the fact that higher predictive power for OLS regressions does not necessarily lead to a better ability to target transfers when using the method of this paper. Specifically, choosing the parameters for β in equation (7) (recall that the functional form of $g(x_i)$ was assumed to be βx_i) that minimize the sum of the squared residuals in a regression ignores the fact that many poverty indices are more sensitive to errors in mis-targeting of transfers among poorer individuals. Ideally, one would like to choose the parameter β which minimizes the poverty index for the sample, instead of minimizing the sum of the squared residuals. This turns out to be more involved than one might think and will be discussed in a future paper. Recall that the papers by Ravallion (1988) and Ravallion and Chao (1988) do minimize poverty directly, but their method does not make efficient use of continuous variables.

A fourth shortcoming of the method presented here is that no behavioral responses are allowed for by the individuals who receive the transfers. For example, some of those who receive them may choose to work fewer hours, so that the increase in income will be reduced (in extreme cases reversed) relative to the case where behavior is fixed.[23/] A further complication, alluded to in Section III, is that once a program of transfers is in place people may change their behavior in order to get more transfers. As far as providing false information, this can usually be handled when the choice of variables is made and when the cost of collecting the new information is calculated.[24/] Perhaps more difficult is that people may actually change their behavior solely for the purpose of obtaining more benefits. Quality of housing and location of residence are two characteristics which individuals may change if they correctly perceive that they will become eligible for transfers by living in lower quality housing or moving to another area (or they may just not make an improvement to their housing - passive eligibility). To the extent that "formulas" can be kept "secret" such behavior, as well as providing false information, can be reduced. Whether the advantages to individuals of making such changes are

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23/ Yet this increase in welfare from increased leisure should not be ignored. Unfortunately, attempts to measure such welfare are both controversial and complex.

24/ But even here one may want to investigate the possibility of using biased but inexpensive information instead of completely throwing it out.

worth the losses involved is an empirical question.[25/]

A final question to be raised is that of administrative feasibility. Implementing household surveys and running regressions such as those presented here is not too difficult for most countries. The difficulties arrive in collecting the data needed from the entire population, as in a census, and in setting up an administrative network to deliver the transfers. Almost all countries have carried out censes, but usually only every 5 to 10 years. Transfer eligibility should be updated more often than that, perhaps on an annual basis. Although many countries have instituted transfer schemes (usually in the form of food rations or food stamps) the administrative success of these is clearly mixed (cf. Alderman, 1988). Some countries may find themselves better equipped to implement such programs than others. On a more optimistic note, technological advances in information technology should reduce many of the implementation costs in the near future.

One last note. This paper has only examined targeting with direct transfers of money, goods, etc. Obviously there are many other kinds of policies which will benefit the poor and can indeed be targeted for their benefit, such as price support policies and the provision of public services (cf. Besley and Ravallion (1988) for an examination of targeted food subsidies). These have not been discussed here in order to focus on some basic issues. Future work on targeting should include any government policies intended to benefit the poor.

[25/] See Nicholas and Zeckhauser (1982) for a discussion of how transfers can be set so that it is not optimal for better off individuals to "masquerade" as poor.

VI. Conclusion

There is a broad consensus in both developed and developing countries that poverty should and can be reduced. However, there is much less consensus on how this can be done. One problem involves the difficulty of ensuring that efforts to assist the poor do indeed reach those who are poor, which is known as the targeting issue. This paper has examined the case where assistance to the poor takes the form of rations, money, vouchers, etc. given directly to individuals or households which have been directly identified as likely to be poor. A formal statement of the problem was presented in Section II.

The main reason targeting is troublesome is that one does not know the incomes of individuals, and there is a clear incentive for them to misrepresent their incomes in order to obtain more tranfers. The third section of this paper presented a simple method for targeting when income (more specifically, households expenditure) is not observable but other characteristics which are correlated with income can be observed. This method was applied using household data from Côte d'Ivoire in Section IV. Using the simplest of regressions techniques on accurate household survey data, one can predict incomes based on observable household characteristics and distribute transfers on the basis of these predictions. For the case of Côte d'Ivoire, substantial reductions in poverty can be made, in some cases relatively close to those possible if income were directly observable. Perhaps of greater interest to policy makers, substantial reductions can be made in the amount of money available for transfers without increasing aggregate poverty if this targeting technique is used, relative to untargeted transfer schemes. Of course, the implementation of this method entails certain costs for gathering information, which may at times outweigh these benefits.

The last section of the paper raised several issues which must be addressed in the future. The method of targeting used here will hopefully be of use not only in designing policies to reduce poverty but also in stimulating further discussion that will lead to better methods. At this point it seems that there is much more that can be done, both at the theoretical and at the policy implementation level, to reduce poverty effectively and efficiently. Even if the method presented here is rejected in favor of another yet to come, the paper will have served its purpose if it contributes to any general discussions which lead to such a future method.

Table 1: **Definitions of Explanatory Variables**

EASTFOR	One if household lives in East Forest region, zero otherwise.
LAREA	Log of floor area square meters of household dwelling.
LPCAREA	Log of floor area (square meters) per capita of dwelling.
HOUSE	One if household lives in single house, zero otherwise.
APT	One if household lives in an apartment, zero otherwise.
WALLWOOD	One if dwelling has wooden walls, zero otherwise.
WALLSTONE	One if dwelling has stone walls, zero otherwise
CEMROOF	One if dwelling has cement roof, zero otherwise.
TOILET	One if household has flush toilet, zero otherwise.
NOCOVER	One if windows of dwelling have no covering, zero otherwise.
FAUCET	One if household's drinking water is from an indoor faucet, zero otherwise.
OPENWELL	One if household's drinking water is from a well with pump, zero otherwise.
VOLTAIC	One if head of household is of Voltaic ethnic group, zero otherwise.
ELEM	One if head of household has elementary level of education, zero otherwise.
JRSEC	One if head of household has junior secondary level of education, zero otherwise.
SRSEC	One if head of household has senior secondary level of education, zero otherwise.
UNIV	One if head of household has university level of education, zero otherwise.
TV	One if household owns TV, zero otherwise.
BIKE	One if household owns bike, zero otherwise.
REF	One if household owns refrigerator, zero otherwise.

Table 2: Urban Regressions

Variable	Models (1)	(2)	(3)	(4)	(5)
Constant	5.212 (25.16)	5.391 (26.96)	5.539 (27.48)	4.076 (46.81)	4.097 (47.70)
EASTFOR	-0.194 (-2.85)	-0.218 (-3.36)	-0.183 (-2.80)	-0.238 (-4.58)	-0.255 (-5.12)
LAREA	0.025 (0.58)	-0.016 (-0.38)	-0.075 (-1.71)	-	-
HOUSE	0.194 (2.43)	0.070 (0.89)	0.151 (1.97)	0.345 (5.96)	0.114 (1.97)
APT	0.143 (1.60)	0.053 (0.61)	0.103 (1.20)	0.345 (5.96)	0.353 (6.31)
WALLWOOD	0.249 (1.58)	0.221 (1.46)	0.245 (1.63)	0.449 (3.77)	0.458 (4.04)
WALLSTONE	0.207 (3.03)	0.143 (2.16)	0.198 (3.01)	0.019 (0.36)	-0.006 (-0.12
CEMROOF	0.577 (6.53)	0.375 (4.25)	0.500 (5.90)	0.239 (3.49)	0.118 (1.75)
TOILET	0.162 (2.19)	0.081 (1.13)	0.100 (1.41)	0.167 (2.97)	0.078 (1.43)
NOCOVER	-0.675 (-1.43)	-0.583 (-1.29)	-0.558 (-1.23)	-0.798 (-2.20)	-0.717 (-2.08)
FAUCET	0.339 (4.61)	0.198 (2.73)	0.212 (2.93)	0.143 (2.60)	-0.006 (-0.124)
OPENWELL	-0.266 (-3.49)	-0.247 (-3.38)	-0.218 (-2.97)	-0.257 (-4.40)	-0.227 (-4.06)
VOLTAIC	-0.187 (-2.14)	-0.162 (-1.93)	-0.187 (-2.23)	-0.142 (-2.12)	-0.133 (-2.08)

(Continued)

Table 2: Urban Regressions (Continued)

Variable	(1)	(2)	(3)	(4)	(5)
ELEM	-	0.096 (1.40)	-	-	0.104 (1.98)
JRSEC	-	0.296 (3.90)	-	-	0.202 (3.43)
SRSEC	-	0.580 (5.80)	-	-	0.272 (3.50)
UNIV	-	0.815 (7.33)	-	-	0.309 (3.50)
CAR	-	-	0.432 (7.08)	-	0.307 (6.54)
BIKE	-	-	-0.076 (-1.20)	-	-0.024 (-0.50)
REF	-	-	0.168 (3.30)	-	0.048 (1.25)
LPCAREA	-	-	-	0.627 (21.48)	0.582 (20.46)
Sample Size	667	667	667	667	667
R^2	0.331	0.393	0.396	0.608	0.654

Table 3: Additional Variables in Regression for Rural Households

WALLADOBE	One if dwelling has adobe walls, zero otherwise.
WALLBAM	One if dwelling has bamboo walls, zero otherwise.
FLOORBAM	One if dwelling has bamboo floors, zero otherwise.
PUMPWELL	One if household's drinking water comes from a well with a pump, zero otherwise.
OPWELLRIV	One if household's drinking water comes from a well without pump or from a river, zero otherwise.
NOWINDOW	One if dwelling has no windows, zero otherwise.
DISTAB, DISTABSQ	The distance by air (kilometers) of the community from Abidjan, and its square, respectively.
LMKTDIST	Log distance (kilometers) to nearest market.
LMANWAGE	Log male agricultural wage rate (thousands CFA Francs per day).
MUSLIM	One if Islam is predominant religion in community, zero otherwise.
COCOAREA	One if cocoa is the leading crop in the community, zero otherwise.
LCOCOHAR	Log household's land (hectares) with mature cocoa trees.
LCAFEHAR	Log household's land (hectares) with mature coffee trees.
LLANDUSE	Log household's land (hectares), excluding cocoa and coffee trees, under cultivation.
AKAN, NMANDE, NONIVOR	Dummy variables which take the value of one if the head of household is an Akan, Northern Mande or Non-Ivorian (i.e. immigrant), respectively, zero otherwise.

Table 4: Rural Regressions

Variable	Models (1)	(2)	(3)	(4)	(5)	(6)
Constant	5.066	11.480	12.055	12.138	10.867	3.135
	(8.66)	(19.26)	(20.60)	(20.98)	(20.90)	(5.77)
LAREA	-0.112	-0.162	-0.118	-0.170	-	-
	(-2.78)	(-4.00)	(-2.92)	(-4.08)		
HOUSE	0.081	0.109	0.075	0.071	0.219	0.286
	(1.52)	(2.04)	(1.40)	(1.34)	(4.71)	(6.09)
APT	0.148	0.210	0.137	0.084	0.503	0.630
	(1.24)	(1.77)	(1.13)	(0.71)	(4.83)	(5.95)
WALLADOBE	-0.068	-0.105	-0.075	-0.067	-0.011	-0.026
	(-1.27)	(-1.97)	(-1.39)	(-1.26)	(-0.22)	(-0.522)
WALLBAM	0.563	0.558	0.543	0.546	0.803	0.876
	(1.22)	(1.24)	(1.18)	(1.21)	(1.85)	(2.07)
FLOORBAM	-0.884	-0.630	-0.894	-0.837	-1.009	-0.787
	(-1.41)	(-1.03)	(-1.43)	(-1.36)	(-1.70)	(-1.36)
TOILET	0.521	0.502	0.498	0.326	0.379	0.197
	(2.11)	(2.07)	(2.01)	(1.29)	(1.61)	(0.822)
PUMPWELL	-0.465	-0.423	-0.469	-0.470	-0.517	-0.478
	(-4.18)	(-3.87)	(-4.22)	(-4.30)	(-4.88)	(-4.61)
OPWELLRIV	-0.329	-0.329	-0.332	-0.332	-0.361	-0.366
	(-2.95)	(-3.01)	(2.99)	(-3.02)	(-3.40)	(-3.53)
NOCOVER	-0.251	-0.233	-0.272	-0.254	-0.138	-0.094
	(-1.79)	(-1.70)	(-1.94)	(-1.84)	(-1.04)	(-0.723)
NOWINDOW	-0.200	-0.182	-0.200	-0.198	-0.057	-0.003
	(-3.70)	(-3.43)	(-3.71)	(-3.73)	(-1.16)	(-0.05)
EASTFOR	-0.323	-0.328	-0.324	-0.326	-0.279	-0.269
	(-4.13)	(-4.27)	(-4.14)	(-4.23)	(-3.76)	(-3.72)
DISTAB*	-3.178	-2.698	-3.238	-3.282	-2.519	-2.100
	(-3.86)	(-3.28)	(-3.93)	(-4.04)	(-3.22)	(-2.69)
DISTABSQ**	3.677	3.256	3.742	3.386	3.018	2.720
	(3.25)	(2.91)	(3.31)	(3.50)	(2.80)	(2.55)
LMANWAGE	0.251	0.303	0.249	0.263	0.209	0.267
	(3.53)	(4.231)	(3.51)	(3.70)	(3.06)	(3.90)
LMKTDIST	-0.038	-0.030	-0.038	-0.031	-0.017	-0.002
	(-1.71)	(-1.37)	(-1.71)	(-1.41)	(-0.83)	(-0.08)
MUSLIM	0.087	0.069	0.082	0.069	0.076	0.029
	(1.23)	(0.98)	(1.16)	(0.98)	(1.13)	(0.43)

Continued

Table 4: Rural Regressions (Continued)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
AKAN	-0.346 (-5.38)	-0.319 (-5.04)	-0.367 (-5.65)	-0.376 (-5.79)	-0.293 (-4.77)	-0.286 (-4.56)
NMANDE	-0.258 (-2.69)	-0.204 (-2.14)	-0.284 (-2.92)	-0.268 (-2.80)	-0.274 (-3.00)	-0.218 (-2.35)
VOLTAIC	-0.525 (-5.09)	-0.467 (-4.51)	-0.539 (-5.22)	-0.583 (-5.32)	-0.542 (-5.52)	-0.473 (-4.48)
NONIVOR	-0.252 (-3.06)	-0.251 (-3.12)	-0.280 (-3.35)	-0.333 (-3.91)	-0.168 (-2.15)	-0.189 (-2.31)
COCOAREA	0.107 (1.72)	0.076 (1.24)	0.116 (1.86)	0.090 (1.46)	0.118 (2.00)	0.083 (1.43)
LCAFEHAR	-	-0.001 (-0.02)	-	-	-	0.016 (0.42)
LLANDUSE	-	0.110 (2.65)	-	-	-	0.133 (3.30)
LCOCOHAR	-	0.107 (2.51)	-	-	-	0.046 (1.13)
ELEM	-	-	0.140 (-2.16)	-	-	-0.059 (-0.97)
JRSEC	-	-	0.043 (0.30)	-	-	-0.089 (0.64)
SRSEC	-	-	0.510 (0.81)	-	-	0.429 (0.74)
CAR	-	-	-	0.545 (4.74)	-	0.338 (3.11)
BIKE	-	-	-	0.042 (1.31)	-	0.006 (0.20)
REF	-	-	-	0.114 (1.09)	-	0.060 (0.59)
LPCAREA	-	-	-	-	0.318 (9.36)	3.135 (5.77)
Sample Size	797	797	797	797	797	797
R^2	0.193	0.228	0.199	0.222	0.268	0.319

Note: Variables with one asterisk (*) are divided by 1,000.
Variables with two asterisks (**) are divided by 1,000,000.

Table 5: Targeting Effectiveness in Urban Côte d'Ivoire

		Poverty Index		
		α = 1	α = 2	α = 3
Initial Poverty Level		0.0757	0.0296	0.0142
T = 10,000,000				
Untargeted		0.0721 (-4.7%)	0.0278 (-6.1%)	0.0131 (-7.7%)
Imperfect Targeting:	Model 1	0.0678 (-10.4%)	0.0248 (-16.3%)	0.0111 (-21.6%)
	Model 2	0.0673 (-11.1%)	0.0242 (-18.3%)	0.0107 (-24.6%)
	Model 3	0.0677 (-10.5%)	0.0247 (-16.5%)	0.0110 (-22.1%)
	Model 4	0.0654 (-13.6%)	0.0239 (-19.5%)	0.0106 (-24.7%)
	Model 5	0.0650 (-14.1%)	0.0233 (-21.2%)	0.0101 (-28.3%)
Perfect Targeting		0.0632 -16.4%	0.0179 (-39.7%)	0.0055 (-61.2%)
T=20,000,000				
Untargeted		0.0688 (-9.1%)	0.0260 (-12.2%)	0.0121 (-14.8%)
Imperfect Targeting:	Model 1	0.0617 (-18.5%)	0.0219 (-26.0%)	0.0095 (-32.8%)
	Model 2	0.0606 (-19.9%)	0.0215 (-27.5%)	0.0094 (-33.8%)
	Model 3	0.0621 (-17.9%)	0.0223 (-24.8%)	0.0098 (-30.8%)
	Model 4	0.0581 (-23.3%)	0.0206 (-30.6%)	0.0088 (-37.8%)
	Model 5	0.0574 (-24.2%)	0.0196 (-33.7%)	0.0080 (-43.2%)
Perfect Targeting		0.0508 (-32.9%)	0.0107 (-63.8%)	0.0024 (-83.2%)

Note: 1. Poverty line = 148,690 CFAF/capita per year.
2. Figures in parentheses show % reduction in poverty, expressed as a negative number given various targeting methods.

Table 6: Poverty Reductions from New Information: Urban Côte d'Ivoire

Initial Information	New Information: Model 1	Model 2	Model 3	Model 4	Model 5	Perfect Information
T = 10,000,000						
1. None (untargeted)						
α = 1	0.0043 (-6.0%)	0.0048 (-6.6%)	0.0044 (-6.1%)	0.0067 (-9.3%)	0.0071 (-9.8%)	0.0089 (-12.3%)
α = 2	0.0030 (-10.8%)	0.0036 (-12.9%)	0.0031 (-11.1%)	0.0039 (-14.1%)	0.0045 (-16.2%)	0.0099 (-35.6%)
α = 3	0.002 (-15.3%)	0.0024 (-18.3%)	0.0021 (-16.0%)	0.0025 (-19.1%)	0.003 (-22.9%)	0.0076 (-58.0%)
2. Model 1						
α = 1	-	0.0005 (-0.7%)	0.0001 (-0.1%)	0.0024 (-3.5%)	0.0028 (-4.1%)	0.0046 (-6.8%)
α = 2	-	0.0006 (-2.4%)	0.0001 (-0.4%)	0.0009 (-3.6%)	0.0015 (-6.0%)	0.0069 (-27.8%)
α = 3	-	0.0004 (-3.6%)	0.0001 (-0.9%)	0.0005 (-4.5%)	0.0010 (-9.0%)	0.0056 (-50.4%)
T = 20,000,000						
1. None (untargeted)						
α = 1	0.0071 (-10.3%)	0.0082 (-11.9%)	0.0067 (-9.7%)	0.0107 (-15.6%)	0.0114 (-16.6%)	0.0180 (-26.2%)
α = 2	0.0041 (-15.8%)	0.0045 (-17.3%)	0.0037 (-14.2%)	0.0054 (-20.8%)	0.0064 (-24.6%)	0.0153 (-58.8%)
α = 3	0.0026 (-21.5%)	0.0027 (-22.3%)	0.0023 (-19.0%)	0.0033 (-27.3%)	0.0041 (-33.9%)	0.0097 (-80.2%)
2. Model 1						
α = 1	- -	0.0011 (-1.8%)	-0.0004 (+0.6%)	0.0036 (-5.8%)	0.0043 (-7.0%)	0.0109 (-17.7%)
α = 2	- -	0.0004 (-1.8%)	-0.0004 (+1.8%)	0.0013 (-5.9%)	0.0023 (-10.5%)	0.0112 (-51.1%)
α = 3	- -	0.0001 (-1.1%)	-0.0003 (+3.2%)	0.0007 (-7.4%)	0.0015 (-15.8%)	0.0071 (-74.7%)

Note: 1. Poverty reductions are in terms of the index in equation (11).

2. Figures in parentheses give the % decrease in poverty, for a fixed set of funds, due to new information (relative to old information), and are expressed in terms of negative numbers.

Table 7: Cost Reductions from New Information: Urban Côte d'Ivoire

Initial Information	New Information: Model 1	Model 2	Model 3	Model 4	Model 5	Perfect Information
T = 10,000,000						
1. None (untargeted)						
α = 1	6,200,000 (-62%)	6,300,000 (-63%)	6,200,000 (-62%)	7,000,000 (-70%)	7,050,000 (-70.5%)	7,100,000 (-71%)
α = 2	7,400,000 (-74%)	7,600,000 (-76%)	7,100,000 (-71%)	8,200,000 (-82%)	8,300,000 (-83%)	8,900,000 (-89%)
α = 3	8,100,000 (-81%)	8,400,000 (-84%)	7,900,000 (-79%)	8,700,000 (-87%)	8,800,000 (-88%)	9,400,000 (-94%)
2. Model 1						
α = 1	-	700,000 (-7%)	100,000 (-1%)	2,600,000 (-26%)	2,800,000 (-28%)	3,700,000 (-37%)
α = 2	-	1,700,000 (-17%)	400,000 (-4%)	2,500,000 (-25%)	3,000,000 (-30%)	6,700,000 (-67%)
α = 3	-	2,300,000 (-23%)	800,000 (-8%)	1,800,000 (-18%)	2,500,000 (-25%)	6,900,000 (-69%)
T = 20,000,000						
1. None (untargeted)						
α = 1	11,400,000 (-57%)	12,000,000 (-60%)	11,800,000 (-59%)	13,800,000 (-69%)	14,100,000 (-70.5%)	14,400,000 (-72%)
α = 2	13,200,000 (-66%)	14,400,000 (-72%)	13,800,000 (-69%)	15,400,000 (-77%)	15,400,000 (-77%)	17,600,000 (-88%)
α = 3	14,500,000 (-72.5%)	15,500,000 (-77.5%)	15,100,000 (-75.5%)	16,700,000 (-83.5%)	16,600,000 (-83%)	18,700,000 (-93.5%)
2. Model 1						
α = 1	-	1,800,000 (-9%)	-800,000 (+4%)	5,500,000 (-27.5%)	5,900,000 (-29.5%)	8,800,000 (-44%)
α = 2	-	1,800,000 (-9%)	-1,500,000 (+7.5%)	4,400,000 (-22%)	6,700,000 (-33.5%)	14,200,000 (-71%)
α = 3	-	1,400,000 (-7%)	-1,700,000 (+8.5%)	4,200,000 (-21%)	7,400,000 (-37%)	16,300,000 (-81.5%)

Note: 1. All cost reductions are rounded to the nearest 100,000 CFA Francs (nearest 50,000 in one case).

2. Figures in parentheses give the % decrease in cost of attaining a given poverty level due to new information (relative to the old information set) and are expressed in terms of negative numbers.

Table 8: Targeting Effectiveness in Rural Côte d'Ivoire

		Poverty Index $\alpha = 1$	$\alpha = 2$	$\alpha = 3$
Initial Poverty Level		0.0884	0.0375	0.0190
T = 10,000,000		0.0836	0.0347	0.0172
Untargeted		(-5.4%)	(-7.5%)	(-9.5%)
Imperfect Targeting:	Model 1	0.0761	0.0298	0.0140
		(-13.9%)	(-20.6%)	(-26.0%)
	Model 2	0.0761	0.0295	0.0137
		(-14.0%)	(-21.2%)	(-27.8%)
	Model 3	0.0770	0.0303	0.0144
		(-12.9%)	(-19.1%)	(-24.3%)
	Model 4	0.0761	0.0296	0.0137
		(-14.0%)	(-21.0%)	(-27.8%)
	Model 5	0.0774	0.0315	0.0155
		(-12.4%)	(-16.0%)	(-18.3%)
	Model 6	0.0777	0.0313	0.0153
		(-12.2%)	(-16.5%)	(-19.5%)
Perfect Targeting		0.0720	0.0217	0.0071
		(-18.6%)	(-42.2%)	(-62.7%)
T = 20,000,000		0.0789	0.0320	0.0155
Untargeted:		(-10.7%)	(-14.7%)	(-18.4%)
Imperfect Targeting:	Model 1	0.0670	0.0251	0.0114
		(-24.2%)	(-32.9%)	(-39.7%)
	Model 2	0.0660	0.0240	0.0104
		(-25.4%)	(-35.8%)	(-45.1%)
	Model 3	0.0680	0.0256	0.0117
		(-23.1%)	(-31.7%)	(-38.0%)
	Model 4	0.0669	0.0245	0.0107
		(-24.3%)	(-34.7%)	(-43.7%)
	Model 5	0.0688	0.0269	0.0129
		(-22.2%)	(-23.3%)	(-31.9%)
	Model 6	0.0693	0.0268	0.0128
		(-21.6%)	(-28.4%)	(-32.6%)
Perfect Targeting		0.0556	0.0119	0.0027
		(-37.2%)	(-68.2%)	(-85.9%)

Note: 1. Poverty line = 87,790 CFAF/capita per year.

2. Figures in parentheses show % reduction in poverty expressed as a negative number given various targeting methods.

Table 9: Poverty Reductions from New Information: Rural Côte d'Ivoire

Initial Information	New Information Model 1	Model 2	Model 4	Perfect Information
T = 10,000,000				
1. None (untargeted)				
α = 1	0.0075 (-9.0%)	0.0075 (-9.0%)	0.0075 (-9.0%)	0.0166 (-13.9%)
α = 2	0.0049 (-14.1%)	0.0052 (-15.0%)	0.0051 (-14.7%)	0.0130 (-37.5%)
α = 3	0.0032 (-18.6%)	0.0035 (-20.3%)	0.0035 (-20.3%)	0.0101 (-58.7%)
2. Model 1				
α = 1	-	0 (0%)	0 (0%)	0.0041 (-5.4%)
α = 2	-	0.0003 (-1%)	0.0002 (-0.67%)	0.0081 (-27.2%)
α = 3	-	0.0003 (-2.1%)	0.0003 (-2.1%)	0.0063 (-49.3%)
T = 20,000,000				
1. None (untargeted)				
α = 1	0.0119 (-15.1%)	0.0129 (-16.3%)	0.0120 (-15.2%)	0.0233 (-29.5%)
α = 2	0.0069 (-21.6%)	0.0080 (-25.0%)	0.0075 (-23.4%)	0.0201 (-62.8%)
α = 3	0.0041 (-26.5%)	0.0051 (-32.9%)	0.0048 (-31.0%)	0.0128 (-82.5%)
2. Model 1				
α = 1	- -	0.0010 (-1.5%)	0.0001 (-0.1%)	0.0114 (-17.0%)
α = 2	- -	0.0011 (-4.4%)	0.0006 (-2.4%)	0.0132 (-52.6%)
α = 3	- -	0.0010 (-8.8%)	0.0007 (-6.1%)	0.0087 (-76.3%)

Note: 1. Poverty reductions are in terms of the index in equation (1).

2. Figures in parentheses give the % decrease in poverty, for a fixed set of funds, due to new information (relative to old information), and are expressed in ter of negative numbers.

Table 10 Cost Reductions from New Information: Rural Côte d'Ivoire

**

Initial Information	New Information Model 1	Model 2	Model 4	Perfect Information
T = 10,000,000				
1. None (untargeted)				
$\alpha = 1$	6,500,000 (-65%)	6,200,000 (-62%)	6,300,000 (-63%)	7,100,000 (-71%)
$\alpha = 2$	7,400,000 (-74%)	7,100,000 (-71%)	7,100,000 (-71%)	9,750,000 (-97%)
$\alpha = 3$	8,100,000 (-81%)	7,700,000 (-77%)	7,800,000 (-78%)	9,300,000 (-93%)
2. Model 1				
$\alpha = 1$	-	0	0	2,500,000 (-25%)
$\alpha = 2$	-	300,000 (-3%)	300,000 (-3%)	6,000,000 (-60%)
$\alpha = 3$	-	400,000 (-4%)	700,000 (-7%)	7,250,000 (-72.5%)
T = 20,000,000				
1. None (untargeted)				
$\alpha = 1$	12,600,000 (-63%)	12,300,000 (-61.5%)	12,400,000 (-62%)	14,200,000 (-71%)
$\alpha = 2$	13,600,000 (-68%)	13,500,000 (-67.5%)	13,500,000 (-67.5%)	17,200,000 (-86%)
$\alpha = 3$	14,300,000 (-71.5%)	14,100,000 (-70.5%)	14,100,000 (-70.5%)	18,400,000 (-92%)
2. Model 1				
$\alpha = 1$	-	1,100,000 (-5.5%)	100,000 (-0.5%)	6,900,000 (-34.5%)
$\alpha = 2$	-	2,300,000 (-11.5%)	1,400,000 (-7%)	12,700,000 (-63.5%)
$\alpha = 3$	-	3,700,000 (-18.5%)	2,700,000 (-13.5%)	15,200,000 (-76%)

Note: 1. All cost reductions are rounded to the nearest 100,000 CFA Francs.

2. Figures in parentheses give the % decrease in cost of attaining a given poverty level due to new information (relative to the old information set) and are expressed in terms of negative numbers.

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